Data Exploration and Analysis: Three Algorithms

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GR5069
Topics in Applied Data Science
for Social Scientists

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Housekeeping

- Today:
  - three algorithms
  - Weekly progress report
  - Second data challenge
- next week:
  - your third progress report
  - Data challenge due at 6PM

Three Algorithms

Algorithm 1: OLS

- what is a regression?

$$E[y|x] = f(x)$$

- where $f(x)$ is a conditional mean function, such that

$$y = E[y|x] + \epsilon$$

- empirically: what do we get from a regression?

Three Algorithms

Algorithm 1: OLS

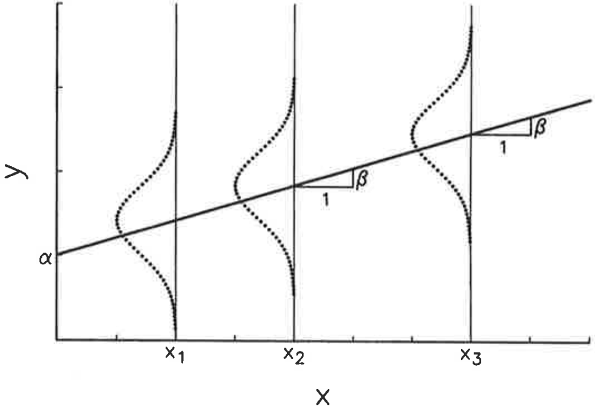


Figure 2.1. Simple Linear Regression Model With the Distribution of y Given x

Figure: Long (1997)

Three Algorithms

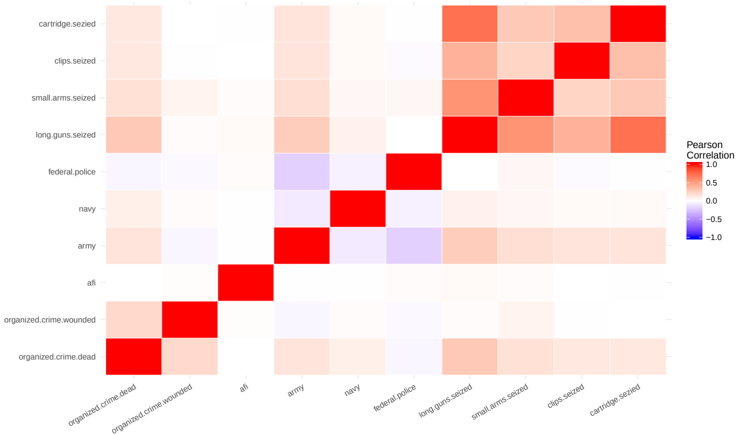
Algorithm 1: OLS

```
Call:
lm(formula = organized.crime.dead ~ organized.crime.wounded +
    afi + army + navy + federal.police + long.guns.seized + small.arms.seized +
    clips.seized + cartridge.seized, data = AllData)

Residuals:
     Min       1Q   Median       3Q      Max
-11.6058  -0.7274  -0.4506   0.2192  27.3262

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)              0.4505553  0.0332307  13.558  < 2e-16 ***
organized.crime.wounded  0.3736900  0.0239171  15.624  < 2e-16 ***
afi                     -0.2261752  0.4210396  -0.537   0.5912
army                     0.3066898  0.0532594   5.758 8.96e-09 ***
navy                     0.7150402  0.1389449   5.146 2.75e-07 ***
federal.police          -0.1271515  0.0773309  -1.644   0.1002
long.guns.seized         0.1478424  0.0085972  17.197  < 2e-16 ***
small.arms.seized       -0.0437447  0.0184592  -2.370   0.0178 *
clips.seized             0.0004374  0.0003152   1.388   0.1653
cartridge.seized        -0.0001690  0.0000193  -8.760  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1  ' ' 1

Residual standard error: 1.731 on 5386 degrees of freedom
Multiple R-squared:  0.1413,Adjusted R-squared:  0.1398
F-statistic: 98.44 on 9 and 5386 DF,  p-value: < 2.2e-16
```

Three Algorithms

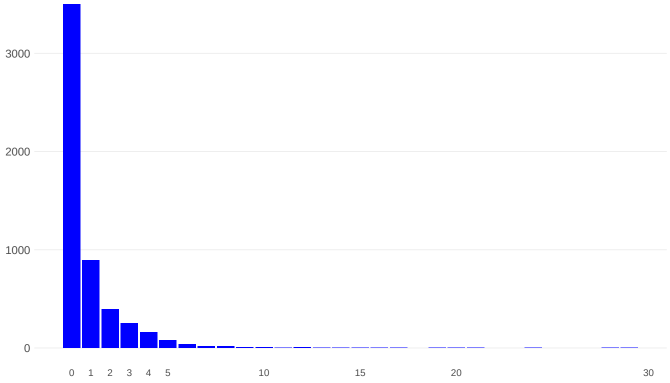
Algorithm 1: OLS

- are these "real" results, or just a mirage from reiterated information in our variables?



Three Algorithms
Algorithm 1: OLS

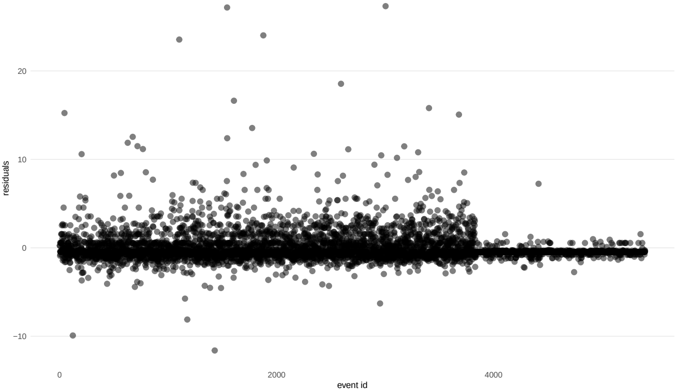
- but wait... what does my DV look like?



Three Algorithms

Algorithm 1: OLS

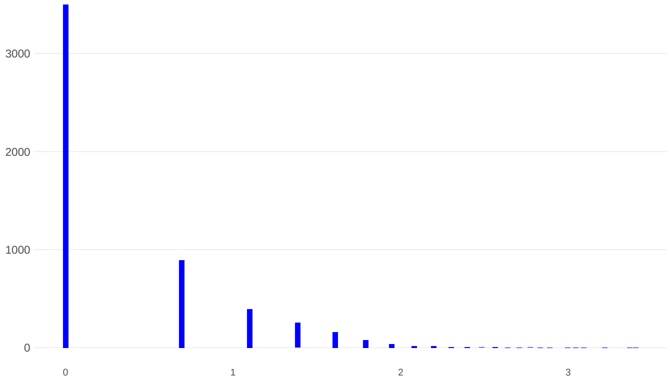
- what's the problem with this?



Three Algorithms

Algorithm 1: OLS

- we can always log it, right?... think again



Three Algorithms

a quick detour: conditional effects

- assume for a moment that this is not problematic
  - (it is! but assume...)
- when analyzing people and behaviors, we're not only concerned about levels
  - we typically care about behaviors *conditional* on something else happening
  - note that this is different from "holding the rest constant"
  - these can be easily computed through **multiplicative interactions**

Three Algorithms

a quick detour: conditional effects

- from the model (with multiplicative interactions)

$$Y = \beta_0 + \beta_X \mathbf{X} + \beta_Z \mathbf{Z} + \beta_{XZ} \mathbf{XZ} + \epsilon$$

- we'd be interested in the marginal effect of Z given X on Y

$$\frac{\partial E[Y|X,Z]}{\partial \mathbf{X}} = \beta_X + \beta_{XZ} \mathbf{Z}$$

Three Algorithms

a quick detour: conditional effects

- going back to our example:
  - **are there more expected deaths when combat is heavier?**
    - let's look at the case of events where the Navy is involved
    - we'd need to assume that more seized heavy weapons indicate heavier combat and compute

$$\beta_{navy} + \beta_{navy,long.guns.seized} * long.guns.seized$$

  - **are there less expected number of deaths when no weapons are seized?**
    - let's look at the case of the Army
    - we maintain the same assumption and compute

$$\beta_{army}$$

Three Algorithms

a quick detour: conditional effects

- but in addition to the marginal effect

$$\frac{\partial E[Y|X,Z]}{\partial \mathbf{X}} = \beta_X + \beta_{XZ}\mathbf{Z}$$

- we also need to compute appropriate standard errors

$$Var\left(\frac{\partial \hat{E}[Y|X,Z]}{\partial \mathbf{X}}\right) = Var[\hat{\beta}_X] + \mathbf{Z}^2 Var[\hat{\beta}_{XZ}] + 2\mathbf{Z}Cov[\hat{\beta}_X, \hat{\beta}_{XZ}]$$

Three Algorithms

a quick detour: conditional effects

```
Call:
lm(formula = organized.crime.dead ~ organized.crime.wounded +
    afi * long.guns.seized + army * long.guns.seized + navy *
    long.guns.seized + federal.police * long.guns.seized + afi *
    cartridge.sezied + army * cartridge.sezied + navy * cartridge.sezied +
    federal.police * cartridge.sezied + small.arms.seized + clips.seized,
    data = AllData)

Residuals:
    Min      1Q  Median      3Q     Max
-8.6509 -0.7385 -0.4189  0.1933 27.2187

Residual standard error: 1.714 on 5378 degrees of freedom
Multiple R-squared:  0.1587,Adjusted R-squared:  0.156
F-statistic: 59.67 on 17 and 5378 DF,  p-value: < 2.2e-16
```

Three Algorithms

a quick detour: conditional effects

```
Coefficients:
                                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)                        0.4188645  0.0336777  12.437  < 2e-16 ***
organized.crime.wounded            0.3624050  0.0237796  15.240  < 2e-16 ***
afi                               -0.0419271  0.5040535  -0.083   0.9337    
long.guns.seized                   0.1713811  0.0172327   9.945  < 2e-16 ***
army                               0.4244453  0.0556353   7.629 2.78e-14 ***
navy                               0.2772627  0.1567621   1.769   0.0770 .  
federal.police                    -0.1113463  0.0801781  -1.389   0.1650    
cartridge.sezied                   0.0002292  0.0000968   2.368   0.0179 *  
small.arms.seized                 -0.0452969  0.0186014  -2.435   0.0149 *  
clips.seized                       0.0003127  0.0003146   0.994   0.3202    
afi:long.guns.seized               0.0229013  0.0784035   0.292   0.7702    
long.guns.seized:army             -0.0459567  0.0181403  -2.533   0.0113 *  
long.guns.seized:navy              0.1761160  0.0421782   4.176 3.02e-05 ***
long.guns.seized:federal.police   -0.0253811  0.0190541  -1.332   0.1829    
afi:cartridge.sezied              -0.0050516  0.0031231  -1.617   0.1058    
army:cartridge.sezied             -0.0003911  0.0000981  -3.987 6.78e-05 ***
navy:cartridge.sezied             -0.0006909  0.0001728  -3.998 6.47e-05 ***
federal.police:cartridge.sezied   -0.0001518  0.0001102  -1.377   0.1685    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Three Algorithms

a quick detour: conditional effects

- marginal effect of 5 seized long guns on the expected number of dead on events that involve the Navy

  1.16
  [-1.17, 3.48]

- marginal effect on the expected number of dead of events that involve the Army when no long guns (zero) are seized

  0.42
  [0.32, 0.53]

Three Algorithms

a quick detour: conditional effects

- Always, always, always remember (Brambor et al. 2006):
  1. Use multiplicative interaction models **whenever one's hypothesis is conditional** in nature.
  2. Include **all constitutive terms** in the model specification.
  3. **Do not interpret the coefficients on constitutive terms as if they are unconditional marginal effects.**
  4. Do not forget to **calculate substantively meaningful marginal effects and standard errors**.
- ... or face the wrath of econometricians

Three Algorithms

Algorithm 2: logistic regression

- different question: **did something happen or not?**
  - essentially, binary outcome classification
  - why not just use OLS?
- one way to think about this: let y^* be a continuous (latent) variable

$$y^* = x\beta + \epsilon$$

- for which we only observe two outcomes

$$y_i = \begin{cases} 1 & if \quad y_i^* > \tau \\ 0 & if \quad y_i^* \leq \tau \end{cases}$$

Three Algorithms

Algorithm 2: logistic regression

- we're interested in the probability that $y = 1$

$$\pi_i = Pr(y = 1) = F(\beta x)$$

- in the case of a logit, we estimate

$$\pi_i = \Lambda(\beta x) = \frac{e^{\beta x}}{1 + e^{\beta x}}$$

- but there's also additional "flavors" (i.e. probit)

Three Algorithms

Algorithm 2: logistic regression

- going back to our example:
  - we have a natural dual category: **events with deaths / no deaths**
  - **could we learn something about correlates to events with organized crime deaths?**
    - we have information on federal forces involved
    - also on materiel seizures
  - **can this relationship ever be causal?**

Three Algorithms

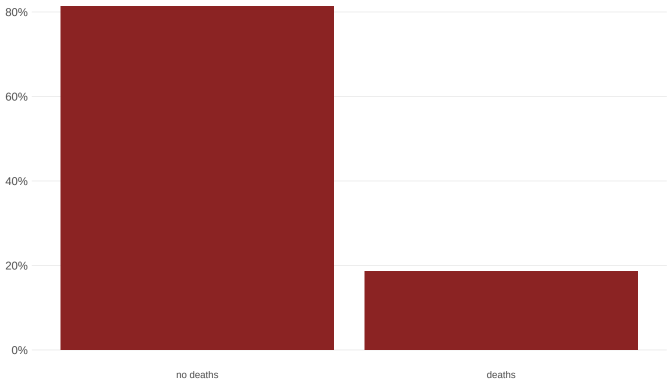
Algorithm 2: logistic regression

```
Call:
glm(formula = organized.crime.death ~ organized.crime.wounded +
    afi + army + navy + federal.police + long.guns.seized + small.arms.seized +
    clips.seized + cartridge.sezied, family = binomial(link = "logit"),
    data = AllData)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-4.5396  -0.6657  -0.4731  -0.4592   2.7612

Coefficients:
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)             -2.1337831  0.0599578 -35.588  < 2e-16 ***
organized.crime.wounded  0.2839835  0.0376519   7.542 4.62e-14 ***
afi                     -0.6960636  0.7234004  -0.962    0.336
army                     0.7395036  0.0812191   9.105  < 2e-16 ***
navy                     0.9292565  0.1827726   5.084 3.69e-07 ***
federal.police          -0.0628413  0.1331772  -0.472    0.637
long.guns.seized         0.1544432  0.0141145  10.942  < 2e-16 ***
small.arms.seized       -0.0137429  0.0271923  -0.505    0.613
clips.seized            -0.0004430  0.0004284  -1.034    0.301
cartridge.sezied        -0.0002413  0.0000510  -4.730 2.25e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1  ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5185.2  on 5395  degrees of freedom
Residual deviance: 4721.3  on 5386  degrees of freedom
AIC: 4741.3
```

Three Algorithms

Algorithm 2: logistic regression

- but wait again, what does my DV look like?



- what does your "plain vanilla" logistic regression assume?

Three Algorithms

Algorithm 3: random forests

- we can also go down the ML path for classification or prediction
  - gaining insight into non-linear relationships (and enhanced predictive power) at cost of interpretability
- popular choice: **random forests**
- simple but powerful algorithm: averages over trees with random selection of features

$$\hat{f}_{rf}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$$

Three Algorithms

Algorithm 3: random forests

- going back to our example:
  - **could we learn something about predictors of organized crime deaths?**
    - we have information on a number of predictors
    - perhaps thinking of this problem as trees may help

Three Algorithms

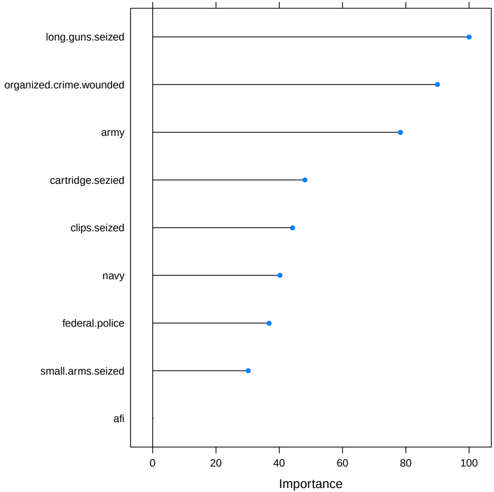
Algorithm 3: random forests

```
randomForest(x = x, y = y, mtry = param$mtry, importance = TRUE, proximity = TRUE)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 2

          Mean of squared residuals: 3.233083
                    % Var explained: 13.77

Random Forest

3778 samples
   9 predictor

Pre-processing: centered (9), scaled (9)
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 3778, 3778, 3778, 3778, 3778, 3778, ...
Resampling results across tuning parameters:

  mtry  RMSE      Rsquared
  2     1.795809  0.1347097
  5     1.836245  0.1213984
  9     1.865167  0.1132198

RMSE was used to select the optimal model using  the smallest value.
The final value used for the model was mtry = 2.
```

Three Algorithms

Algorithm 3: random forests

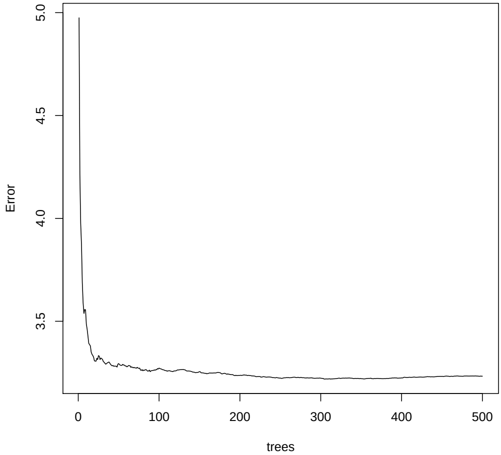
- what does variance importance tell us?



Three Algorithms

Algorithm 3: random forests

- a quick look at MSE for this model



Three Algorithms

What did we learn from these algorithms?

- **OLS**
  - **navy** participation and **organized crime wounded** are highly associated with levels of organized crime deaths
  - number of **long guns seized** in events where navy participated had no effect on levels of organized crime deaths
- **logistic regression**
  - **navy** participation and **organized crime wounded** are highly associated with having organized crime deaths in an event
- **random forests**
  - number of **long guns seized** and **organized crime wounded** are the best predictors of deaths in events
- all of these conclusions, within the known limitations of the data (and the analyses)

Weekly Progress Review

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